

Day 2: Data structures and databases

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Introduction to Data Science and Big Data Analytics

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Day 2 Outline

Big Data

- Business intelligence

- Architecture

Data types and structures

Dataset manipulation

Data bases

- Relational data bases

- Normal forms

Compression

Big Data

From Wiki

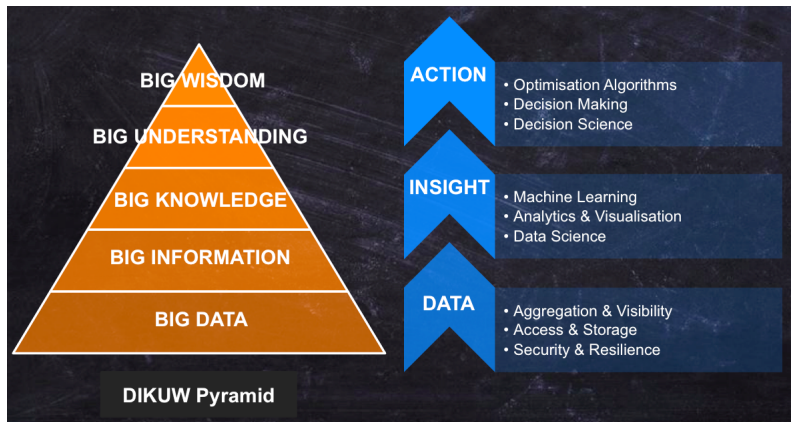
- ▶ Volume: big data doesn't sample; it just observes and tracks what happens
- ▶ Velocity: big data is often available in real-time
- ▶ Variety: big data draws from text, images, audio, video; plus it completes missing pieces through data fusion
- ▶ Machine Learning: big data often doesn't ask why and simply detects patterns
- ▶ Digital footprint: big data is often a cost-free byproduct of digital interaction

Components of Big Data

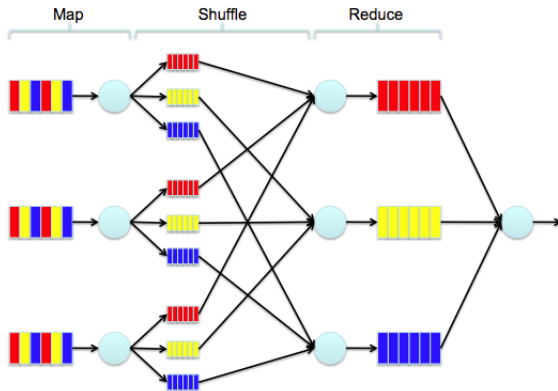
McKinsey report:

- ▶ Techniques for analyzing data (A/B testing, machine learning, natural language processing)
- ▶ Big Data technologies, like business intelligence, cloud computing and databases
- ▶ Visualization.

Business intelligence



MapReduce

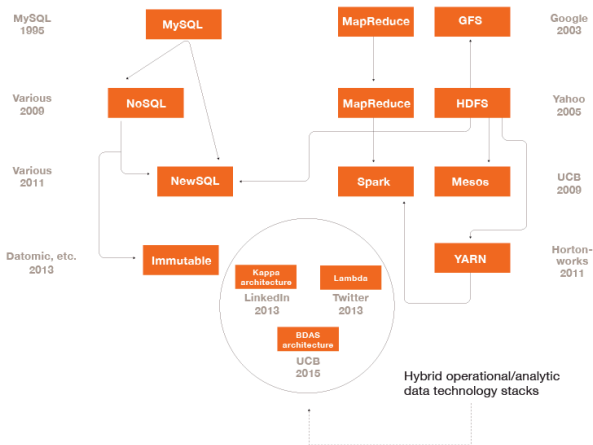


Architecture evolution

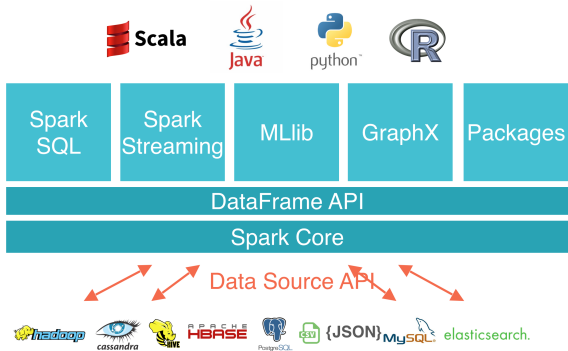
Distributed data architecture timelines and database evolution

Siloed OLTP/OLAP
web app database paradigms

Ad hoc batch/microbatch analytics
and the unsiloed data lake paradigm



Typical data analytic stack



Data types and structures

What is “data science”?

- ▶ extraction or generation of knowledge from data
- ▶ extends “data mining”, using computational and algorithmic methods
- ▶ combines applied statistical methods with advances in computer science, especially machine learning
- ▶ may involve “unstructured” data, especially text, but also video and images
- ▶ closely tied to computational methods

Why focus on data types and structures?

- ▶ "data" mining and "data" science imply that we know how to work with data
- ▶ data structures are not neutral - they shape how we record, see, and have the ability to analyze information
- ▶ much of the actual work in data mining and data analysis is done at the data "munging" stage

Basic (atomic) data types in R

numeric 8-byte numeric representations

integer non-floating point numbers

character text

logical TRUE or FALSE

Recursive types also exist, such as lists and vectors; there are also special classifications for NA

Basic data types in R: integer

```
x <- 10
typeof(x)

## [1] "double"

is.integer(x)

## [1] FALSE

x <- 7L           # force integer type
typeof(x)

## [1] "integer"

object.size(x)

## 48 bytes

as.integer(3.14)

## [1] 3
```

Basic data types in R: character

```
typeof("test string")  
  
## [1] "character"  
  
object.size("a")  
  
## 96 bytes  
  
s <- ""                                # Unicode  
cat(s)  
  
##  
  
as.character("3.14")    # coerce numerics to character  
  
## [1] "3.14"
```

Basic data types in R: numeric

```
x <- 10.5      # assign a numeric value
x              # print the value of x

## [1] 10.5

typeof(x)      # print the class name of x

## [1] "double"

object.size(x) # show storage size in bytes

## 48 bytes
```


is.*() and as.*()

```
is.numeric(x)      # is the object of numeric type?
```

```
## [1] TRUE
```

```
is.numeric(7.1)
```

```
## [1] TRUE
```

```
is.numeric("7.1")
```

```
## [1] FALSE
```

```
is.numeric(as.numeric("7.1"))
```

```
## [1] TRUE
```

Basic data types in R: logical

A logical value is 'TRUE' or 'FALSE', often created via comparison between variables.

```
1 < 2                # is 1 less 2

## [1] TRUE

x <- c(1, 2, 3)
y <- c(4, 3, 2)
x > y                # vectorized comparison

## [1] FALSE FALSE  TRUE

typeof(x > y)

## [1] "logical"
```

Difference between 'mode' and 'class'

- ▶ 'atomic' modes are numeric, complex, character and logical
- ▶ recursive objects have modes such as 'list' or 'function' or a few others
- ▶ an object has one and only one mode
- ▶ 'class' is a property assigned to an object that determines how generic functions operate with it - not a mutually exclusive classification
- ▶ an object has no specific class assigned to it, such as a simple numeric vector, it's class is usually the same as its mode, by convention
- ▶ an object's mode can be changed through coercion, without necessarily changing the class

Numerical precision issues

- ▶ floating point numbers are approximations of numbers
 - ▶ precision: anything more than 16 base-10 digits must be approximated
 - ▶ fractions: approximated if not $\frac{x}{2^k}$
 - ▶ anything over stated precision is truncated: $3.57\text{e}21 + 1 = 3.57\text{e}21$

```
1 - 4/5 - 1/5  # not zero!
```

```
## [1] -5.551115e-17
```

Machine limits

```
.Machine$integer.max
```

```
## [1] 2147483647
```

```
.Machine[c("double.xmin", "double.xmax", "double.digits")]
```

```
## $double.xmin
```

```
## [1] 2.225074e-308
```

```
##
```

```
## $double.xmax
```

```
## [1] 1.797693e+308
```

```
##
```

```
## $double.digits
```

```
## [1] 53
```

Alternatives (Stata)

- ▶ single and double precision:
<http://blog.stata.com/2012/04/02/the-penultimate-guide-to-precision/>
- ▶ R has only double precision

Common input formats

- ▶ csv
- ▶ Excel
- ▶ "fixed formats"
- ▶ relational databases
- ▶ embedded tags: Extensible Markup Language (XML)
- ▶ key-value pair schemes (JSON)
 - ▶ examples of JSON and XML: <http://json.org/example>

Special issue: text encoding

- ▶ a “character set” is a list of character with associated numerical representations
- ▶ ASCII: the original character set, uses just 7 bits (2^7) – see http://ergoemacs.org/emacs/unicode_basics.html
- ▶ ASCII was later extended, e.g. ISO-8859
<http://www.ic.unicamp.br/~stolfi/EXPORT/www/ISO-8859-1-Encoding.html>, using 8 bits (2^8)
- ▶ but this became a jungle, with no standards:
http://en.wikipedia.org/wiki/Character_encoding

Solution: Unicode

- ▶ Unicode was developed to provide a unique number (a "code point") to every known character – even some that are "unknown"
- ▶ problem: there are more far code points than fit into 8-bit encodings. Hence there are multiple ways to *encode* the Unicode code points
- ▶ *variable-byte* encodings use multiple bytes as needed. Advantage is efficiency, since most ASCII and simple extended character sets can use just one byte, and these were set in the Unicode standard to their ASCII and ISO-8859 equivalents
- ▶ two most common are **UTF-8** and **UTF-16**, using 8 and 16 bits respectively

Warnings with text encodings

- ▶ Input texts can be very different
- ▶ Many text production software (e.g. MS Office-based products) still tend to use proprietary formats, such as Windows-1252
- ▶ Windows tends to use UTF-16, while Mac and other Unix-based platforms use UTF-8
- ▶ Your eyes can be deceiving: a client may display gibberish but the encoding might still be as intended
- ▶ No easy method of detecting encodings (except in HTML meta-data)

Dataset manipulation

What is a “Dataset”?

- ▶ A dataset is a “rectangular” formatted table of data in which all the values of the same variable must be in a single column
- ▶ Many of the datasets we use have been artificially reshaped in order to fulfill this criterion of rectangularity

Revisting basic data concepts

- ▶ The difference between tables and *datasets*

Revisting basic data concepts

- ▶ The difference between tables and *datasets*
- ▶ This is a (partial) **dataset**:

district	incumbf	wonseatf	
1	Carlow	Kilkenny	Challenger Lost
2	Carlow	Kilkenny	Challenger Lost
5	Carlow	Kilkenny	Incumbent Won
100	Donegal	South West	Challenger Lost
459		Wicklow	Incumbent Won
464		Wicklow	Challenger Lost

Revisiting basic data concepts

- ▶ The difference between tables and *datasets*
- ▶ This is a (partial) **dataset**:

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- ▶ This is a **table**:

	Lost	Won
Challenger	266	60
Incumbent	32	106

Revisting basic data concepts

- ▶ The difference between tables and *datasets*
- ▶ This is a (partial) **dataset**:

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- ▶ This is a **table**:

	Lost	Won
Challenger	266	60
Incumbent	32	106

- ▶ The key with a dataset is that **all the values of the same variable must be in a single column**

Example: Comparative Manifesto Project dataset

Note: Available from <https://manifestoproject.wzb.eu/>

```
# load in a subset of the Manifesto Project dataset, with counts  
load(url("http://kenbenoit.net/files/cmpdata.Rdata"))  
# View(cmpdata)
```

Example: Comparative Manifesto Project dataset

This is “wide” format:

	country	countryname	oecdmember	eumember	edate	date	party	partyname
203	42	Austria	10	10	2008-09-28	200809	42320	SPOE Social Democratic Party
204	42	Austria	10	10	2008-09-28	200809	42110	Green Party
205	42	Austria	10	10	2008-09-28	200809	42520	OVP: People's Party
206	42	Austria	10	10	2008-09-28	200809	42420	FPO: Freedom Party
207	42	Austria	10	10	2008-09-28	200809	42710	BZO Alliance for the Future of Austria
208	42	Austria	10	10	2008-09-28	200809	42220	KP<d6> Communist Party of Austria
314	21	Belgium	10	10	1991-11-24	199111	21521	CVP Christian People's Party
315	21	Belgium	10	10	1991-11-24	199111	21111	ECOLO Francophone Ecologists
316	21	Belgium	10	10	1991-11-24	199111	21321	SP Flemish Socialist Party
317	21	Belgium	10	10	1991-11-24	199111	21522	PSC Christian Social Party
318	21	Belgium	10	10	1991-11-24	199111	21421	PVV Party of Liberty and Progress
319	21	Belgium	10	10	1991-11-24	199111	21913	VU People's Union
320	21	Belgium	10	10	1991-11-24	199111	21912	FDF Francophone Democratic Front

Long v. wide formats

- ▶ reshape
 - ▶ the “old” R way to do this, using ‘base::reshape()’
 - ▶ problem: confusing and difficult to use
- ▶ reshape2
 - ▶ from Hadley Wickham’s reshape2 package
 - ▶ data is first ‘melt’ed into long format
 - ▶ then ‘cast’ into desired format

Example: wide to long using reshape2

```
require(reshape2, quietly = TRUE)
# this will select only the "per" variables for measurement
cmpdataLong <- melt(cmpdata,
                    id.vars = c("countryname", "party", "date"),
                    measure.vars = names(cmpdata)[21:76],
                    variable.name = "category",
                    value.name = "catcount")

# why do this?
cmpdataLong$category <- as.character(cmpdataLong$category)
# View(cmpdataLong)
```

Example: wide to long using reshape2

```
require(reshape2, quietly = TRUE)
# now we can get summary statistics across countries, e.g. for economic
with(subset(cmpdataLong, grepl("^per7", category)),
      table(countryname, category))
```

##	category						
## countryname	per701	per702	per703	per704	per705	per706	
## Austria	34	34	34	34	34	34	
## Belgium	63	63	63	63	63	63	
## Cyprus	10	10	10	10	10	10	
## Denmark	60	60	60	60	60	60	
## Finland	47	47	47	47	47	47	
## France	23	23	23	23	23	23	
## Germany	30	30	30	30	30	30	
## Great Britain	20	20	20	20	20	20	
## Greece	17	17	17	17	17	17	
## Iceland	31	31	31	31	31	31	
## Ireland	31	31	31	31	31	31	
## Israel	32	32	32	32	32	32	
## Italy	41	41	41	41	41	41	
## Luxembourg	21	21	21	21	21	21	
## Malta	4	4	4	4	4	4	
## Netherlands	48	48	48	48	48	48	
## Norway	28	28	28	28	28	28	
## Portugal	38	38	38	38	38	38	

A better way

```
require(dplyr, warn.conflicts = FALSE, quietly = TRUE)
cmpdataLong2 <- melt(select(cmpdata, countryname, party, date, per101:per706),
  id.vars = c("countryname", "party", "date"),
  # NOT NEEDED measure.vars = names(cmpdata)[21:76],
  variable.name = "category",
  value.name = "catcount")
cmpdataLong2$category <- as.character(cmpdataLong2$category)
identical(cmpdataLong, cmpdataLong2)

## [1] TRUE
```

A better way

```
with(filter(cmpdataLong2, grepl("^per7", category)),  
      table(countryname, category))
```

##	category
## countryname	per701 per702 per703 per704 per705 per706
## Austria	34 34 34 34 34 34
## Belgium	63 63 63 63 63 63
## Cyprus	10 10 10 10 10 10
## Denmark	60 60 60 60 60 60
## Finland	47 47 47 47 47 47
## France	23 23 23 23 23 23
## Germany	30 30 30 30 30 30
## Great Britain	20 20 20 20 20 20
## Greece	17 17 17 17 17 17
## Iceland	31 31 31 31 31 31
## Ireland	31 31 31 31 31 31
## Israel	32 32 32 32 32 32
## Italy	41 41 41 41 41 41
## Luxembourg	21 21 21 21 21 21
## Malta	4 4 4 4 4 4
## Netherlands	48 48 48 48 48 48
## Norway	28 28 28 28 28 28
## Portugal	38 38 38 38 38 38
## Spain	57 57 57 57 57 57
## Sweden	44 44 44 44 44 44

Grouping operations: number of parties per election

```
# group by country-election
by_country <- group_by(cmpdataLong, countryname, date)
nparties <- summarise(by_country, npart = n())
head(nparties)
```

```
## Source: local data frame [6 x 3]
```

```
## Groups: countryname [1]
```

```
##
```

```
##   countryname   date npart
```

```
##   <chr>   <int> <int>
```

```
## 1   Austria 199010   224
```

```
## 2   Austria 199410   280
```

```
## 3   Austria 199512   280
```

```
## 4   Austria 199910   224
```

```
## 5   Austria 200211   280
```

```
## 6   Austria 200610   280
```

```
# is that correct?
```


Grouping operations: number of parties per election corrected

```
# group by country-election
by_country_unique <- distinct(cmpdataLong, countryname, date, party)
by_country_n <- group_by(by_country_unique, countryname, date)
nparties <- summarise(by_country_n, npart = n())
head(nparties, 10)
```

```
## Source: local data frame [10 x 3]
```

```
## Groups: countryname [2]
```

```
##
```

```
##      countryname    date npart
```

```
##           <chr>   <int> <int>
```

```
## 1      Austria 199010     4
```

```
## 2      Austria 199410     5
```

```
## 3      Austria 199512     5
```

```
## 4      Austria 199910     4
```

```
## 5      Austria 200211     5
```

```
## 6      Austria 200610     5
```

```
## 7      Austria 200809     6
```

```
## 8      Belgium 199111    11
```

```
## 9      Belgium 199505    10
```

```
## 10     Belgium 199906     9
```

Grouping operations: number of parties per election final

```
# using "chaining" -- no need for intermediate objects
nparties2 <- distinct(cmpdataLong, countryname, date, party) %>%
  group_by(countryname, date) %>%
  summarise(npart = n())
identical(nparties, nparties2)

## [1] TRUE
```

Databases

Relational data bases

- ▶ invented by E. F. Codd at IBM in 1970
- ▶ A relational database is a collection of data organized as a set of formally defined tables
- ▶ These tables can be accessed or reassembled in many different ways without having to reorganize the underlying tables that organize the data
- ▶ RDBMS: a relational database management system.
Examples include: MySQL, SQLite, PostgreSQL, Oracle. MS Access is a lite version of this too.
- ▶ The standard user and application programmer interface to a relational database is **structured query language** (SQL)

Example

- ▶ example: Database of Parties, Elections, and Governments (DPEG) relational database

```
SELECT c.countryName, c.countryAbbrev, p.* FROM party AS p
      LEFT JOIN country AS c
      ON p.countryID = c.countryID
```

- ▶ simpler example: convert CMP data into relational tables for countries, parties, elections, categories, and counts

Basic relational structures

- ▶ tables
 - ▶ also known as “relations”
 - ▶ tables define the forms of the data that are linked to other data through key relations
- ▶ keys: how tables are cross-referenced
 - ▶ primary key: an column in a table that uniquely identifies the remaining data in the table
 - ▶ foreign key: a field in a relational table that matches the primary key column of another table
 - ▶ join operations link tables in a structured query

Normal forms 1

“Normalizing” a database means creating a proper set of relations

First normal form: No Repeating Elements or Groups of Elements

```
head(select(cmpdata, countryname, partyname, date, per108, per110))
```

##	countryname	partyname	date	per108	per110
## 175	Austria	FP Freedom Party	199010	3	0
## 176	Austria	GA Green Alternative	199010	0	3
## 177	Austria	SP Social Democratic Party	199010	5	0
## 178	Austria	VP People's Party	199010	8	0
## 179	Austria	FP Freedom Party	199410	1	11
## 180	Austria	LF Liberal Forum	199410	0	0

Here, this is violated because of the wide format of per108 and per110. To solve this, we have to move this to long format.

Normal forms 2

Second normal form: No Partial Dependencies on a Concatenated Key

```
head(cmpdataLong)
```

##	countryname	party	date	category	catcount
## 1	Austria	42420	199010	per101	0
## 2	Austria	42110	199010	per101	0
## 3	Austria	42320	199010	per101	0
## 4	Austria	42520	199010	per101	5
## 5	Austria	42420	199410	per101	0
## 6	Austria	42421	199410	per101	0

Here, the format is still violated, because party 42420 is repeated. To solve this we need to create a party table and link to it using a foreign key.

Normal forms 3

Third normal form: No Dependencies on Non-Key Attributes.

Every non-prime attribute of data in a table must be dependent on a primary key.

```
head(cmpdataLong)
```

##	countryname	party	date	category	catcount
## 1	Austria	42420	199010	per101	0
## 2	Austria	42110	199010	per101	0
## 3	Austria	42320	199010	per101	0
## 4	Austria	42520	199010	per101	5
## 5	Austria	42420	199410	per101	0
## 6	Austria	42421	199410	per101	0

Here, this is violated because election data repeats across multiple values of the category count table, when it should have its own table.

Non-relational data

- ▶ recently popularized because so much data is unstructured, and dealing with new data forms in a classic relational setting requires changing the entire schema
- ▶ non-relational systems typically define data using **key-value** pairs
- ▶ example: JSON - see <http://kenbenoit.net/files/JSONexample.json>

Compression: sparse matrix format

Compression: sparse matrix format

used because many forms of matrix are very sparse - for example, document-term matrixes

```
require(quanteda, warn.conflicts = FALSE, quietly = TRUE)
```

```
## quanteda version 0.9.8
```

```
myDfm <- dfm(inaugTexts, verbose = FALSE)
myDfm[1:10, 1:5]
```

```
## Document-feature matrix of: 10 documents, 5 features.
```

```
## 10 x 5 sparse Matrix of class "dfmSparse"
```

```
##               features
## docs      fellow-citizens  of the senate and
## 1789-Washington           1  71 116           1  48
## 1793-Washington           0  11  13           0   2
## 1797-Adams                3 140 163           1 130
## 1801-Jefferson            2 104 130           0  81
## 1805-Jefferson            0 101 143           0  93
## 1809-Madison              1  69 104           0  43
## 1813-Madison              1  65 100           0  44
## 1817-Monroe               5 164 275           0 122
## 1821-Monroe               1 197 360           0 141
## 1825-Adams                0 245 304           0 116
```

Compression: sparse matrix format

used because many forms of matrix are very sparse - for example, document-term matrixes

```
# how many cell counts are zeros
sum(myDfm==0) / (ndoc(myDfm) * nfeature(myDfm)) * 100

## [1] 91.67661

object.size(myDfm)

## 1125120 bytes

object.size(as.matrix(myDfm))

## 4762560 bytes
```